Evaluating Soil Color with Farmer Input and Apparent Soil Electrical Conductivity for Management Zone Delineation

K. L. Fleming,* D. F. Heermann, and D. G. Westfall

ABSTRACT

Variable rate fertilizer application technology (VRT) can provide an opportunity to more efficiently utilize fertilizer inputs; however, accurate prescription maps are essential. Researchers and farmers have understood the value of dividing whole fields into smaller, homogeneous regions or management zones for fertility management. Management zones can be defined as spatially homogeneous subregions within a field that have similar crop input needs. Delineating management zones that characterize the spatial variability within a field may provide effective prescription maps for VRT. The objective of this research was to compare and evaluate management zones developed from soil color (SC) and farmer experience with management zones developed from apparent electrical conductivity (EC$_a$). These two methods of developing management zones were compared with soil nutrient levels, texture, and crop yields collected on two fields in 1997. The soil and yield parameters followed the trends indicated by both management zone methods at Field 1 with the highest values found in the high productivity zones and the lowest the low productivity zones. Significant differences were found among the management zones. However, at Field 2 the high and medium productivity zones were generally not significantly different using the SC approach, whereas the EC$_a$ approach was effective in identifying three distinct management zones. Both methods of developing management zones seem to be identifying homogeneous subregions within fields.

ACCURATE PRESCRIPTION MAPS are essential for effective VRT fertilizer application (Sawyer, 1994; Ferguson et al., 1996). Researchers and farmers have understood the value of dividing whole fields into smaller, homogeneous regions or management zones for fertility management. A management zone for VRT application can be defined as a subregion of a field that expresses a homogeneous combination of yield limiting factors for which a single rate of a specific crop input is appropriate (Doerge, 1999). Delineating management zones that characterize the spatial variability within a field may provide effective prescription maps for VRT.

Earlier studies proposed the division of fields by soil type (Carr et al., 1991). Their work indicated that applying different fertilizer treatments to contrasting soils in a field can generate greater returns than applying a field average fertilizer treatment. Mausbach et al. (1993) concluded National Cooperative Soil Survey is not adequate for variable rate application. Soil surveys were not intended for precision farming and tend to map at scale too coarse to be effective. Franzen et al. (2002) compared Order 1 and Order 2 soil surveys with maps from grid sampling and topography based zone maps. Order 2 soil surveys were seldom useful in determining zones for site specific management of NO$_3$–N. Order 1 soil surveys were more highly related to soil NO$_3$–N than Order 2 surveys, but their consistency was not as high as when topography based zones or maps from grid sampling were used. Landscape position also has been used to divide fields (Fiez et al., 1994). They found that landscape position alone was not effective in dividing fields into units for variable rate N management. However, Franzen et al. (2001) concluded that topography-based zone soil sampling may be useful in semiarid environments. Long et al. (1998) proposed using the spatial variation in grain protein levels to identify N management zones in spring wheat (*Triticum aestivum* L.). Currently, the procedure is applicable for dryland fields that are cropped annually to wheat. Practical implementation of this procedure requires that an appropriate sensor be made available to producers that can continuously read the protein concentration of grain from combine harvester. Ostergaard (1997) developed management zones for VRT N application based on soil type, yield, topography, aerial photos, and producer experience. Five fields were divided into 12 to 17 management zones. The zones were soil sampled to determine N rate. They found a $15 to $35 per hectare economic advantage using variable rate N application. Fleming et al. (2001) describe the application of soil color and farmer knowledge to define management zones for variable rate fertilizer application. Initial analysis indicates that this method is effective in identifying different management zones. However, ground truthing is needed to develop accurate VRT maps from the zones.

DEVELOPING MANAGEMENT ZONES

Method 1: Soil Color with Farmer Input

The spectral properties of bare soil surfaces are largely governed by soil organic matter (SOM) and moisture (Schreier et al., 1988). The gray tone pattern in black and white aerial photographs is often a reflection of these soil properties and may be linked to productivity (McCann et al., 1996). Chen et al. (2000) found that remotely sensed imagery of a bare soil field could be quantified to describe the spatial variation of SOM. Predicted SOM was highly correlated with measured

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Abbreviations: EC, electrical conductivity; EC$_a$, apparent electrical conductivity; GPS, global positioning systems; OLS, ordinary least squares model; SC, soil color; SOM, soil organic matter; SPA, spatial auto regressive model; VRT, variable rate fertilizer application technology.

SOM. The technology and methodology were simple and accurate enough to be of practical use in agricultural production fields. Using LANDSAT images, Bhatti et al. (1991) reported SOM distribution highly correlated with the spatial distribution determined by grid sampling the surface soil. In addition, the semivariograms for the two methods of determining SOM were similar. More importantly, the SOM content was significantly correlated to winter wheat yield. These data suggest that SOM determined by aerial photographs or remote sensing may be used to determine site-specific management zones.

Scientists know that the experiences of farmers have been extremely important in the development of agriculture as we know it today (Crookston, 1996). If it were not for farmers' experiential decision-making, most of the modern agriculture that we take for granted today would be unknown. Dr. Crookston has spent several years working with agricultural researchers. It was his observation that the family farm has been a valuable research enterprise, each generation has studied its alternatives and made its decisions. Unfortunately, the potential contributions of farmer knowledge to soil and crop research is not being fully utilized today. Farmers generally know which areas of a field produce high yields and which areas are low in production. It is logical that nutrient needs are different for these areas. This allows identification of different management zones in a field using farmer knowledge as one of the predictors.

Method 2: Apparent Electrical Conductivity

Electrical conductivity (EC) is the ability of a material to transmit (conduct) an electrical current. Apparent electrical conductivity mapping has been useful in locating saline seeps in the northern Great Plains (Halvorson and Rhoades, 1974) and for diagnosing salinity-related problems in the irrigated Southwest (Rhoades and Corwin, 1981). Researchers also have used soil EC to measure or estimate many other chemical and physical properties of nonsaline soils. Williams and Hoey (1987) found that EC strongly correlates to soil texture. In addition to its ability to identify variations in soil texture, electrical conductivity has proven to relate closely to other properties that often determine a field's productivity (Lund et al., 1999). These include water content (Kachanoski et al., 1988), cation exchange capacity and exchangeable Ca and Mg (McBride et al., 1990), depth to claypans (Kitchen et al., 1999), soil organic C (Jaynes, 1996), and herbicide behavior in soil (Jaynes et al., 1994). Sudduth et al. (1995) found strong correlations between EC_a and depth to claypan and yield. Heermann et al. (1999) reported that EC_a was the best predictor of crop yield when compared with many other common soil and crop parameters. Soil classification using EC_a provides an effective basis for delineating interrelated physical, chemical, and biological soil attributes (Johnson et al., 2001). With the advent of global positioning systems (GPS), practitioners can now place EC_a measuring devices on GPS-equipped field vehicles and create EC_a maps for all types of agricultural soils. These maps can be the basis for developing management zones for VRT. The objective of this paper is to compare and evaluate prescription maps developed from soil color and farmer experience with prescription maps developed from EC_a.

MATERIALS AND METHODS

Field studies were conducted in 1997 on two center pivot irrigated fields in northeastern Colorado to assess the technical and economic feasibility of precision farming. Data from these locations will be discussed and used to evaluate the management zones. The area of Field 1 was 71 ha and Field 2 was 52 ha. Soils in both fields included a Valentine sand (sandy, mixed nonacid, mesic Typic Ustipsamments), a Bijou loamy sand (coarse loamy, mixed, mesic Mollic Haplargids), and a Truckton loamy sand (coarse loamy, mixed, mesic Udic Argiustolls) (Soil Survey Staff, 1996). These are nonsaline soils. The fields were in continuous corn (*Zea mays* L.) throughout the study. Each field has been managed and operated by the same two farmers since 1977. Irrigation strategy was based on experience, no formal scheduling program was used. Fertility management was based on soil sampling and experience. All nutrients have been applied uniformly at these fields.

Aerial 35-mm bare soil photographs obtained from USDA Farm Service Agency flights were used as an initial template in developing the soil color with farmer input management zones. The bare soil photographs were geo-registered and enhanced to contrast color differences using AgriTrak Professional software (Agritrak, 1998). The farmers then drew vector lines on the photographs using AgriTrak Professional based primarily on differences in soil color to establish the individual high, medium, and low productivity management zones. The decision to delineate three management zones was made by the farmers. Their logic was they felt in some areas of the field they had been applying adequate levels of crop inputs for optimum production while in others application rates applied were too high and too low for optimum production, leading to their choice of three management zones. A recent study using a quantitative clustering approach to develop management zones found that maximizing the variability between zones was achieved when the number of zones was three or less (Fridgen et al., 2004). After initially defining the soil color zones on their personal computers, each farmer drove over the fields and made qualitative adjustments in the zone boundaries on laptop computers based on topography changes and their production experience on the fields.

To develop the EC_a management zones, Fields 1 and 2 were mapped using a GPS equipped Veris model 3100 conductivity sensor (Lund and Christy, 1998). The Veris system identifies soil variability by directly sensing soil electrical conductivity. As the cart is pulled through the field, a pair of coulter electrodes transmit an electrical current into the soil, while two other pairs of coulter electrodes measure the voltage drop. The measurement electrodes are configured to measure EC_a over an approximate 0- to 30-cm depth (shallow reading) as well as a 0- to 90-cm depth (deep reading). The system georeferences the EC_a measurements using an external Trimble ag32 DGPS receiver, and stores the resulting data in digital form.

Data were collected in April 1998 on transects spaced approximately 10 m apart on a l-s interval, corresponding to a measurement every 3 to 5 m along the transects. This procedure resulted in a data density of 200 to 300 points per hectare.

Clustering was used to group the EC_a measurements into management zones. The objective of cluster analysis is to statistically minimize the within-group variability while max-

imizing the among-group variability to produce homogeneous groups that are definitive from one another.

The shallow, deep, and difference between the shallow and deep EC_a point readings were used for the cluster analysis; zones with the highest, intermediate, and lowest EC_a values were defined as high, medium, and low productivity zones, respectively. These data were standardized to a mean of 0 and standard deviation of 1 to bring all data to a standard measurement scale. The analyses were performed using Ward's Minimum Variance method using SAS statistical software (SAS Inst., 1990). This method is an agglomerative hierarchical clustering technique (initial clusters are formed from pairing of individual cases; subsequent clusters are formed from joining pairs of previous clusters and/or cases; clustering continues until all clusters/cases are joined into one cluster). Ward's method, as many clustering methods, is sensitive to outliers. Consequently, the algorithm was instructed to keep 10% of the most "different" cases out of clustering process. The clustered point data was then interpolated using proximity and smoothed using nine nearest neighbor majority in ArcView (ESRI, 1994) to create the final management zones.

Soil sampling was completed in April 1997 on a 76-m grid over both fields. The surface 0 to 0.2 m was analyzed for NO_3, NH_4, P, K, Zn, pH, SOM, and texture. Subsoil samples from 0.3- to 0.6-, 0.6- to 0.9-, and 0.9- to 1.2-m increments were analyzed for NO_3–N.

The fields were yield mapped with two Case IH Axial Flow combine harvesters equipped with Micro-Trak yield monitors. Location data were collected on a 1-s interval using an Ashtech Super C/A receiver GPS system in differential mode. The GPS system was a 12 channel receiver. All the GPS positional data were based on the World Geodetic System of 1984 (WGS84). The GPS data was differentially corrected with a base station set near the experimental field. Yield data were processed and mapped using Farmers Software Harvest Mapping System (Redhen Systems, 1996).

An analysis of variance was performed on the soil and yield data from the management zones using S-PLUS statistical software (Mathsoft, 1995). Initially an ordinary least squares model (OLS) was used; when spatial autocorrelation between observations existed, a spatial auto regressive model (SPA) was used. Spatial autocorrelation was measured using Moran's I (Moran, 1950). The Moran's I is used to test for the presence of spatial autocorrelation in a two-dimensional plane. In this study, the null hypothesis is that the measurements of soil and yield data are independent of one another in space. Moran's I is a dimensionless statistic and can be interpreted as a Pearson product-moment correlation between variables x and y. The index generally ranges over the interval of -1 to $+1$, but can exceed these limits if an irregular pattern of weights has been used or extreme values are heavily weighted (Bonham and Reich, 1999).

The spatial weight matrix used in the spatial model was based on inverse distance squared. The null hypothesis of no significant differences between management zones was tested by the ANOVA model

$$Y(ij) = y.. + a(i) + e(ij)$$

where $y..$ is the grand mean of all observations, $a(i)$ is the effect of the ith management zone, and $e(ij)$ are independent random errors. Equality of means by management zone was tested with a restatement of the ANOVA model in the form of a regression model

$$Y(ij) = y.. + b0 + b1 \times a1 + b2 \times a2 + e(ij)$$

where

$a1 = 1$ if high productivity management zone
$a1 = 0$ if medium productivity management zone
$a1 = -1$ if low productivity management zone
$a2 = 1$ if medium productivity management zone
$a2 = 0$ if high productivity management zone
$a2 = -1$ if low productivity management zone

When spatial autocorrelation exists in a data set the assumption of independent observations in a classical model is violated. This can underestimate the standard errors, resulting in increased overall significance between individual parameters or overestimate the standard error resulting in an overall lack of significance when one exists (Bonham and Reich, 1999). All of the soil sample data points were spatially joined to their respective management zones for the analysis of variance. For the spatially dense yield data the points were averaged in 30 by 30 m pixels and then spatially joined to their respective management zones. This was necessary for the spatial analysis in S-PLUS. The spatial algorithms are too complex to analyze very large data sets such as the complete yield and EC_a on personal computers available at this time. Data pixels that fell into more than one management zone were dropped.

RESULTS AND DISCUSSION

Field 1

When comparing the two methods the management zones and results of the analysis of variance were similar on this field with the following common observations (Fig. 1).

Levels of SOM and crop yield were significantly different across all management zones. Nitrate and K levels were significantly different between the high/low and high/medium zones while Zn levels were significantly different between the high and low productivity zones. Phosphorus did not follow the trends seen with the other nutrients, with higher levels seen in the lower productivity zones and lower levels in the high productivity zones (Tables 1 and 2).

Soil texture showed similar trends. Clay and silt levels were higher in the high productivity zone, intermediate in the medium zones, and lowest in the low productivity zones while sand followed the opposite trend using both methods (Table 3). Differences were significant between all texture classes with the SC method; however, differences were not significant between the high and medium zones using the EC_a method.

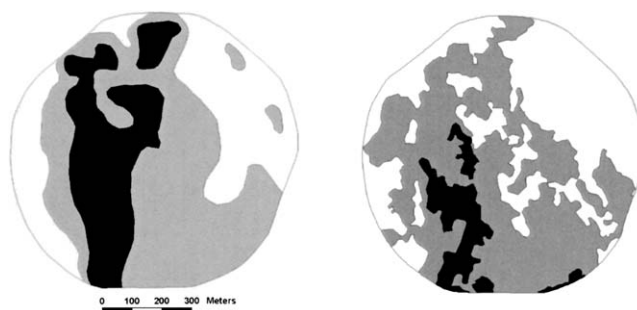Higher productivity in areas of lower sand and higher

Fig. 1. Field 1 management zones–soil color with farmer input management zones on the left and apparent electrical conductivity management zones on the right (low productivity = white, medium productivity = gray, high productivity = black).

Table 1. Soil color (SC) and apparent electrical conductivity (SC$_a$) at Field 1. Analysis of variance of soil organic matter (SOM), NO$_3$–N, and P as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

Management zone	SOM				NO$_3$–N			P	
	n	%	SD	n	mg kg^{-1}	SD	n	mg kg^{-1}	SD
					SC				
1	35	0.8a*	0.03	35	18a	1.3	35	16a	0.9
2	57	1.0b	0.02	57	20a	1.1	57	11b	0.8
3	29	1.2c	0.03	29	25b	1.5	29	14a	1.1
Model	SPA†				SPA			OLS‡	
$Pr > F$	0.0001				0.0001			0.001	
					EC$_a$				
1	52	0.85a	0.02	52	17a	1.1	52	13a	0.8
2	57	1.0b	0.02	57	20a	1.1	57	13a	0.8
3	13	1.2c	0.05	13	30b	2.2	13	13a	1.7
Model	SPA				OLS			SPA	
$Pr > F$	0.0001				0.0001			0.0001	

* Means followed by different letters are significantly different at $p < 0.05$.
† Spatial auto regressive model.
‡ Ordinary least squares model.

Table 2. Soil color (SC) and apparent electrical conductivity (SC$_a$) at Field 1. Analysis of variance of K, Zn, and yield as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

Management zone	K				Zn			Yield	
	n	mg kg^{-1}	SD	n	mg kg^{-1}	SD	n	Mg ha^{-1}	SD
					SC				
1	35	142a*	6.6	35	3.8a	0.2	639	9.8a	0.2
2	57	160a	5.2	57	4.1ab	0.1	963	10.7b	0.1
3	29	207b	7.2	29	4.4b	0.2	474	10.8c	0.2
Model	SPA†				SPA			SPA	
$Pr > F$	0.0001				0.001			0.0001	
					EC$_a$				
1	52	148a	6.0	52	4.0a	0.1	926	9.8a	0.1
2	57	166a	5.7	57	4.1ab	0.1	1080	10.7b	0.1
3	13	224b	12.0	13	4.5b	0.3	168	10.8c	0.2
Model	SPA				OLS‡			SPA	
$Pr > F$	0.0001				0.01			0.0001	

* Means followed by different letters are significantly different at $p < 0.05$.
† Spatial auto regressive model.
‡ Ordinary least squares model.

clay levels would be expected due to the higher water holding and cation exchange capacity of the soils higher in clay.

These results are similar to the findings of Mulla and Bhatti (1997). They concluded that in terms of practicality, organic matter estimated from bare soil images offer the best feasibility in dividing fields into management zones

The Moran's I for the raw data was significant across all parameters, indicating the data are spatially auto correlated. In general the spatial model had slightly lower standard error and higher r^2 using both management zone approaches. However, the spatial model was not always significantly better than the OLS. With the SC method the Likelihood ratios were not significant for P, sand, silt, and clay while with the EC$_a$ approach the Likelihood ratios were not significant for NO$_3$, Zn, and silt. The Moran's I for the residuals of these parame-

Table 3. Soil color (SC) and apparent electrical conductivity (SC$_a$) at Field 1. Analysis of variance of sand, silt, and clay as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

Management zone	Sand				Silt			Clay	
	n	%	SD	n	%	SD	n	%	SD
					SC				
1	35	88.4a*	0.009	35	4.2a	0.007	35	7.4a	0.008
2	57	85.2b	0.007	57	5.6b	0.006	57	9.2b	0.006
3	29	81.8c	0.010	29	9.4c	0.008	29	10.8c	0.009
Model	OLS†				OLS			OLS	
$Pr > F$	0.0001				0.0001			0.0001	
					EC$_a$				
1	13	87.7a	0.009	13	4.5a	0.006	13	7.7a	0.008
2	57	83.8b	0.006	57	6.3b	0.005	57	10.0b	0.006
3	52	81.5b	0.014	52	7.8c	0.007	52	10.7b	0.009
Model	SPA‡				OLS			SPA	
$Pr > F$	0.0001				0.0001			0.0001	

* Means followed by different letters are significantly different at $p < 0.05$.
† Ordinary least squares model.
‡ Spatial auto regressive model.

Table 4. Soil color (SC) and apparent electrical conductivity (SC$_a$) at Field 2. Analysis of variance of SOM, NO$_3$–N, and P as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

Management zone		SOM			NO$_3$–N			P	
	n	%	SD	n	mg kg^{-1}	SD	n	mg kg^{-1}	SD
					SC				
1	38	0.96a*	0.02	38	11a	0.7	38	11a	0.7
2	28	1.15bc	0.02	28	14bc	0.8	28	15bc	0.9
3	22	1.09c	0.02	22	14c	0.8	22	15c	1.0
Model		OLS†			SPA‡			OLS	
$Pr > F$		0.0001			0.0001			0.001	
					EC$_a$				
1	39	0.95a	0.01	39	11a	0.6	39	11a	0.8
2	27	1.13b	0.02	27	13b	0.8	27	15a	0.9
3	22	1.14b	0.02	22	15b	0.9	22	14.b	1.0
Model		OLS			SPA			OLS	
$Pr > F$		0.0001			0.0001			0.02	

* Means followed by a different letters are significantly different at $p < 0.05$.
† Ordinary least squares model.
‡ Spatial auto regressive model.

Table 5. Soil color (SC) and apparent electrical conductivity (SC$_a$) at Field 2. Analysis of variance of K, Zn, and yield as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

Management zone		K			Zn			Yield	
	n	mg kg^{-1}	SD	n	mg kg^{-1}	SD	n	Mg ha^{-1}	SD
					SC				
1	38	162a*	5.1	35	2.2a	0.06	735	11.2a	0.2
2	28	218bc	5.9	57	2.7bc	0.08	500	14.1b	0.3
3	22	199c	6.7	29	2.7c	0.09	372	13.1c	0.3
Model		OLS†			OLS			SPA‡	
$Pr > F$		0.0001			0.0001			0.0001	
					EC$_a$				
1	39	159a	4.5	39	2.2a	0.06	637	11.0a	0.2
2	27	203b	5.4	27	2.8b	0.08	605	13.4b	0.2
3	22	226c	6.0	22	2.7b	0.09	358	13.7c	0.3
Model		OLS			OLS			SPA	
$Pr > F$		0.0001			0.0001			0.0001	

* Means followed by different letters are significantly different at $p < 0.05$.
† Ordinary least squares model.
‡ Spatial auto regressive model.

ters was also not significant, indicating the management zones are accounting for the spatial autocorrelation in these parameters.

It is interesting how similar the SC management zones that were defined using a qualitative supervised classification with our cooperating farmers are to the EC$_a$ management zones that were defined using a quantitative unsupervised classification. The two methods seem to be capturing similar information in this field.

Field 2

Results of the spatial analysis of variance for the SC method on Field 2 indicated that the soil and crop parameters were different across the management zones; however, they did not follow the trends indicated by the farmer-developed zones. The zone classified as medium in productivity was highest in SOM, K, yield, and clay, while the high productivity zones had intermediate values for these parameters. The low productivity zone had the lowest values for the parameters listed above and were highest in sand (Tables 4, 5, and 6). In addition, no significant difference was detected between the high and medium productivity zones for the soil parameters discussed above. This would seem to indicate this method is only defining two zones in this field.

The results from Field 2 illustrate the SC method is

consistently identifying different productivity subregions within the field; however, it indicates the subregions need to be ground truthed to classify them as management zones. The management zones developed from EC$_a$ indicate why the trends in the SC approach changed. The patterns of the zones from both methods are quite similar; however, the EC$_a$ zones reveal significant inclusions of high productivity soils in the area that was defined as medium with the SC approach. There are also inclusions of medium productivity soils in the area defined as high in productivity with the SC method (Fig. 2).

All of the soil and crop parameters followed the trends indicated by the management zones. Crop yield, K, sand, silt, and clay were significantly different across all three zones using the EC$_a$ method (Tables 4, 5, and 6).

Other studies have also shown that clustering algorithms can be effective in developing management zones. Stafford et al. (1998) used yield maps to regionalize fields into management units. The clustering procedure they used recognized subregions of the fields with distinct patterns of season to season variation in yields. Boydell and McBratney (1999) found that a number of consecutive years of remotely sensed cotton (*Gossypium hirsutum* L.) yield estimates clustered to generate regions of similarity for management zones. Shatar and McBratney (2001) used a *k* means cluster analysis on

Table 6. Soil color (SC) and apparent electrical conductivity (SC$_a$) at Field 2. Analysis of variance of sand, silt, and clay as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

Management zone	Sand			Silt			Clay		
	n	%	SD	n	%	SD	n	%	SD
					SC				
1	38	84.4a*	0.008	38	7.3a	0.006	38	8.3a	0.007
2	28	75.4b	0.009	28	13.3cb	0.008	28	11.4b	0.008
3	22	78.7c	0.010	22	11.6c	0.006	22	9.7ab	0.009
Model	OLS†			OLS			OLS		
$Pr > F$	0.0001			0.0001			0.0001		
					EC$_a$				
1	39	84.5a	0.007	39	7.6a	0.007	39	7.9a	0.006
2	27	78.4b	0.008	27	11.4b	0.008	27	10.1b	0.007
3	22	74.5c	0.009	22	13.3c	0.009	22	12.1c	0.008
Model	SPA‡			OLS			SPA		
$Pr > F$	0.0001			0.0001			0.0001		

* Means followed by different letters are significantly different at $p < 0.05$.
† Ordinary least squares model.
‡ Spatial auto regressive model.

sorghum [*Sorghum bicolor* (L.) Moench] yields, soil organic C, and soil K to subdivide fields into homogeneous units. The algorithm presented showed some promise for identifying spatially contiguous zones, which are more homogenous in soil properties than the whole field. Yang and Anderson (1996) also had success using clustering to classify management zones. In this study color infrared digital video images of two grain sorghum fields in south Texas were acquired and classified into management zones using unsupervised classification. Their analysis of variance showed that plant biomass and yield differed significantly among their management zones.

The results from the Moran's I analysis on the raw data was similar to Field 1 with all of the parameters being spatially auto correlated using both methods. However, the Moran's I for the residuals of most of the soil parameters was not significant, indicating the management zones for the most part were accounting for the spatial correlation in the data in this field. The exceptions were NO_3 in both zone delineation methods and sand and clay with the EC$_a$ method. The Likelihood ratios were significant for these parameters, indicating the spatial model was significantly better.

SUMMARY AND CONCLUSIONS

Both methods of developing management zones seem to be identifying homogeneous subregions within fields. However, in Field 2 the EC$_a$ approach was more effective in identifying three distinct management zones. The

Moran's I analysis indicated the data were spatially auto correlated. On Field 1 the analysis was mixed with certain soil parameters the OLS model was adequate; with others a spatial auto regressive model was needed. On Field 2 the OLS model was adequate; the MZ accounted for the spatial correlation for the most part in this field. This analysis has identified the large scale spatial variability between zones for each method. However, further analysis is needed to evaluate the small scale spatial variability within zones to determine which method is characterizing the fields most accurately. An intense small scale cluster sampling technique within each zone is needed to accomplish this. Based on this initial evaluation it appears EC$_a$ is more consistent in identifying different management zones across fields. Differences in the effectiveness of soil color with farmer input management zones between fields may be due to the selective skills of the different farmers in recognizing zone boundaries. Further testing over a broader scope of fields, farmers, and crop production systems is needed to confirm these results. In the future, methods using the information from both EC$_a$ and soil color along with farmer knowledge may provide the most effective management zones.
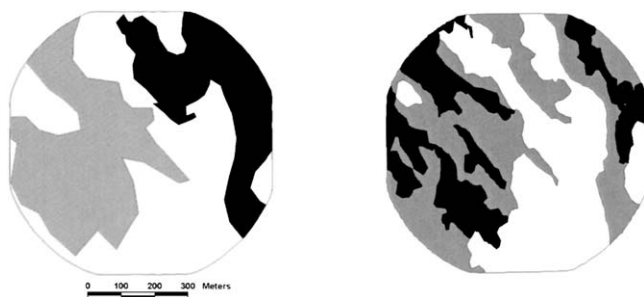
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Fig. 2. Field 2 management zones–soil color with farmer input management zones on the left and apparent electrical conductivity management zones on the right (low productivity = white, medium productivity = gray, high productivity = black).

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